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Applied forensic epidemiology: The Bayesian evaluation of forensic evidence in vehicular homicide investigation

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ABSTRACT

The comparative weighting of evidence in a criminal case can be a complicated task when the relevance or meaning of the evidence is disputed. An example of this complexity in seen in vehicular homicide investigations in which the identity of the driver (and thus the guilty party) is not clear. The discipline of Forensic Epidemiology, including the appropriate application of Bayes' Theorem (Bayes' Law) provides a systematic framework to bring clarity to the evaluation of such matters. Bayes' is a useful tool for the conditioning and quantification of probabilities associated with evidence in a vehicular homicide investigation. The authors present a case study in the application of Bayes' Theorem to the facts in a vehicular homicide investigation. An initial analysis of the crash dynamics in comparison with the injury pattern and ejection status of the surviving occupant versus that of the decedent suggested that the survivor was the driver. The results of the analysis were used as tests for guilt, with estimated true and false positive rates, which then formed the basis for a Bayesian calculation of the posterior probability of the survivor's guilt given the evidence. As a result of the Bayesian analysis described herein, it was determined that the survivor was 19 times more likely to have been the driver, in comparison with the decedent. This ratio far exceeded the suggested threshold of 10:1 for establishing the guilt of the survivor beyond a reasonable doubt. When used properly, Bayes' Theorem can offer definitive insight in the investigation and prosecution of vehicular homicide cases.

1. Introduction

Forensic epidemiology is defined as the "proper application of epidemiologic concepts and data to forensic issues,"[1] a definition that includes the use of probability in evaluating evidence and data in disputed matters. A unique application for the principles of Forensic epidemiology is seen in disputed matters that have only two possible solutions that are mutually exclusive. Heightened clarity is possible in such cases primarily because the fact finder is presented with only two outcomes from which to choose, and any evidence in support of one outcome is evidence against the other, essentially doubling the probative weight of validated evidence.

An example of this dichotomy occurs in vehicular homicide investigations in which two occupants of the same vehicle are ejected, one dies, and the surviving (and typically intoxicated) occupant claims that the decedent was the driver. In such a scenario, any evidence indicating that the decedent was a passenger serves as equally weighted evidence that the survivor was the driver, and vice versa.

A critical issue in all criminal forensic investigations is the *relevance* of an analytic outcome to the question of whether the defendant is guilty or innocent, referred to as the "ultimate question" for brevity. Maximally relevant or "ideal" evidence refers to evidence that most directly relates to the ultimate question in a case.[2] With ideal evidence, there is a 1:1 ratio of evidence weight to ultimate question weight; as an example, if there is 95% probability that the evidence interpretation is correct then there is 95% certainty of guilt. An example of ideal evidence is breathalyzer evidence of alcohol intoxication in a driver: To the extent that the test is reliable, it is an indication of both blood alcohol concentration *and* guilt. In contrast, minimally relevant or "useless" evidence is poorly correlated to the ultimate question of guilt or innocence.[2] An example of useless evidence is an admission by a defendant in a rape case that he had previously viewed pornographic materials, as the association between the propensity to commit rape and the propensity to view pornography is non-causal.[3]

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While most forensic evidence falls somewhere between ideal and useless, evidence of who was driving in a vehicular homicide case with two occupants (one decedent, and one intoxicated survivor) can be very close to ideal. The probability of the guilt of the survivor is equal to the probability that he was the driver, and the probability that he is innocent is equal to the probability that he was the passenger.

A potential difficulty for fact finders in vehicular homicide cases arises from the lack of reliability and precision associated with injury pattern evidence. Occupant injury patterns are often used in a vehicular homicide investigation to help determine where an occupant was seated during a collision, as some injuries are more commonly associated with a driver's position than a passenger's position, and vice versa.[4] The difficulty occurs when there are differing expert interpretations of the significance of the injuries. As an example, a defense expert may claim that a chest abrasion seen in a decedent was caused by contact with a steering wheel and therefore the surviving defendant must have been the passenger and thus not guilty. In contrast, a prosecution expert may claim that the abrasion could have been caused by contact with a variety of surfaces and thus suggests neither guilt nor innocence. The jury is then left with two differing interpretations and no means of quantitatively comparing the accuracy of one to the other.

Prior research has described how the use of injury patterns derived from post-mortem and medical record evidence of decedents and survivors can be systematically paired with crash reconstruction, occupant kinematic evidence, and epidemiologic data concerning the correlation between injury patterns and crash types. This methodology, referred to as injury pattern analysis (IPA), can help illuminate pertinent details of a vehicular homicide case, such as occupant position.[4] While prior publications on IPA have focused on what type of evidence may be used for such an analysis or more precise methods of identifying injury patterns,[5] what has been lacking previously is a method of quantifying the probabilities associated with the evidence.

Probability is used to characterize the degree of belief in the truth of an assertion regarding evidence. The simplest approach to probability is that of the Frequentist, in which prior observation is used to predict a future or unknown event. An example of a Frequentist conclusion is that 81% of known offenders in the UK are men.[6] While this fact allows for the conclusion that 19% of the next 10,000 crimes committed in the UK will be committed by a woman it does not allow for any conclusion regarding a particular crime. The probability that a crime was committed by a woman versus a man may be altered by circumstances that could substantially affect the probability, i.e. if the crime occurred in an all women's prison.

2. Bayes' theorem

For circumstances in which a variety of conditions exist that may modify or "condition" the probability of a particular outcome or scenario, a more appropriate approach is that of the Bayesist, named for the Bayes' theorem or Law upon which the approach is based. Most simply stated, Bayes' Law allows for a more precise quantification of the uncertainty in a given probability. As applied in a forensic setting, Bayes' law tells us what we want to know given what we do know.[7] Bayes' law is named for the essay by Reverend Thomas Bayes (1702–1761) on the statistical analysis of probability, presented as a series of 10 propositions.[8] Over the past 250 years, subsequent authors have further defined and refined Bayes' propositions. The publications of DV Lindley, in particular, advanced both the understanding of the various applications of Bayes' law as well as potential pitfalls in the use of the approach.[9,10] With regard to forensic applications, Dawid has written extensively on the use of Bayes' theorem and other statistical arguments.[11,12] Although Bayes' law is known in forensic science primarily for its application to DNA evidence, Dawid has greatly advanced the use of Bayes' as a means of helping fact finders understand the impact of evidence using probability in a variety of applications, given the various ways that evidence can interact.[13]

Bayes' law is, at its most simple, $P(A|B)$ in which the probability of A is dependent upon condition B (for example, the probability of drawing an ace of spades from a deck of cards given that only black cards can be selected is 1:26). It is relatively unusual to find evidence in a dispute matter that is not conditioned by variables that affect the probability associated with the evidence, and for this reason a Bayesian rather than Frequentist approach is often desirable in a forensic setting. For example, a Frequentist conclusion regarding seat belt use is that they improve survivability in traffic crashes. Applied to a particular traffic fatality in which no seat belt was used, the Frequentist approach would lead to the conclusion the use of a seat belt would have decreased the probability of death. If the seat belt use question was conditioned by the fact that the collision was a near side impact (e.g. a driver's-side crash to an occupant in the driver's seat) in which seat belts do not affect injury frequency, then the Frequentist approach would result in an incorrect conclusion that would have been avoided by the proper conditioning of the probability of injury given seat belt use by impact direction.

For the vehicular homicide case with only two possible solutions (survivor is driver and thus guilty or survivor is passenger and thus innocent) much of the evidence in support of one solution or the other is most appropriately interpreted as conditional probabilities, and for this reason a Bayesian approach is well suited to such scenarios. This is particularly true with regard to injury patterns observed in occupants in vehicular homicides, as evidenced by both the post-mortem evidence in the case of the decedent and the contemporaneous medical evidence of injury in the case of the surviving occupant.

In this paper we present a vehicular homicide scenario with a mutually exclusive outcome in which a Bayesian analysis proved to be particularly helpful in quantifying the certainty of the conclusions. The application of Bayes' law can be somewhat counter-intuitive at times, and for this reason it is best to use a relatively straightforward example to introduce some basic concepts. Consider the case of a worker who sustained a serious on-the-job injury in which evidence suggested an equipment malfunction. In order to support an allegation of contributory negligence on the part of the worker, the employer produced the results of a post-incident drug screen that was positive for a stimulant that is a controlled substance. The critical question in the case is how conclusive is the test, given the accuracy characteristics of the test. The accuracy of the test is defined in terms of the test's ability to identify the drug as present when it is (the sensitivity) and to identify the drug as being absent when it is not present (the specificity). The question for the fact finder is, what is the probability that the injured worker was under the influence of a controlled substance at the time of the injury given the accuracy of the test?

Suppose that the sensitivity of the test is 0.99 (99% of the time the drug is present the test is positive [true positive], and 1% of the time it is present the test is negative) and the test specificity is 0.95 (95% of the time the drug is absent the test is negative and 5% of the time it is absent the test is positive [false positive]). These values represent conditional probabilities – the probability of a positive test given the presence of the stimulant and the probability of a negative test given the absence of the stimulant. Given the very high probability (99%) that the test will correctly identify the drug presence there is an intuitive temptation to fall into what is known as the Prosecutor's Fallacy, in which it is assumed that the 99%

sensitivity translates to a 99% probability that the worker had the drugs in his system at the time of the incident, and that the potential error rate is a negligible 1%. The Prosecutor's Fallacy results from the failure to condition a probability when needed; put another way, the Prosecutor's Fallacy occurs when a Frequentist's approach is used when a Bayesian approach is more appropriate. It is also a classic example of a conditional probability fallacy; the conclusion that the probability of *A* given *B* is the same as the probability of *B* given *A*, where *A* and *B* represent events such as a positive drug test and the presence of drugs in the individual with the positive test.[14] The error in this reasoning is illustrated with a simple example of a drug test that is positive if the test subject licks a piece of paper and it is found to be wet. The test would have a sensitivity of 100% as all test subjects with drugs in their system would test positively. The obvious flaw with the test is that it would have 0% specificity, as all test subjects would have a positive result, regardless of their drug status. A conditional probability fallacy would occur if the correct conclusion that drug presence will be detected 100% of the time the test is administered was reversed, and it was concluded that 100% of the time the test was positive that drugs were present.

ing into account all of the associative data along with the positive test results. In the equation above it is important to note that the resulting posterior probability depends not only on the drug test sensitivity and specificity but also the unconditioned probability of drug presence prior to knowing anything about the drug test result (known as the prior probability), denoted as $P(\text{Drugs})$ in the equation above. The prior probability is the prevalence of drug presence among the population representative of the injured worker; i.e. workers who are injured on the job. The converse of $P(\text{Drugs})$ is $P(\text{No Drugs})$, the prevalence of no drugs in the representative population, or $[1 - P(\text{Drugs})]$. The posterior probability that the worker was under the influence of drugs given the positive drug test, denoted as $P(\text{Drugs}|\text{Pos})$ in the equation, represents a conditioning of the prior probability $P(\text{Drugs})$ to reflect the evidentiary weight of the positive drug test.

For the purposes of the example we will assume that of all workers injured on the job the prevalence of drug presence among them is 0.02 or 2%. With this piece of information we can then calculate the probability that the worker was under the influence of the drug given the positive drug test, or $P(\text{Drugs}|\text{Pos})$, using the following values:

$$\text{Prior probability} = P(\text{Drugs}) = 0.02$$
$$[\text{1-prior probability}] = P(\text{No Drugs}) = 0.98$$
$$\text{True positive rate} = P(\text{Pos} \mid \text{Drugs}) = 0.99$$
$$\text{False positive rate} = P(\text{Pos} \mid \text{No Drugs}) = 0.05$$
$$P(\text{Drugs} \mid \text{Pos}) = \frac{(\text{sensitivity}) \times (\text{prevalence})}{(\text{sensitivity}) \times (\text{prevalence}) + (1 - \text{specificity}) \times (1 - \text{prevalence})}$$

Bayes' law provides the probabilistic framework for correctly assessing the strength of associative data – in the present example, the positive drug test – and has been applied in a variety of forensic venues.[15,16] Bayes' law can be stated symbolically as

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A \mid B)P(B) + P(A \mid \bar{B})P(\bar{B})}$$

where $\bar{B}$ represents the converse of B. Thus, if B represents the condition when drugs are present, then $\bar{B}$ (literally "not B") represents the condition when drugs are not present. Thus, the probability of a positive test when drugs are present (the test sensitivity) is represented by $P(A|B)$ and the probability of a positive test when drugs are not present is represented by $P(A|\bar{B})$ in the lower right hand part of the equation. This figure is calculated by subtracting the specificity figure of 0.95 from 1 (0.05 or 5%). If the test correctly identifies 95% of samples with no drugs present as negative, it then incorrectly identifies 5% of samples with no drugs present as positive.

Translated for the drug testing example, Bayes' law can be used to arrive at the result of interest, the probability of drugs given a positive test.

$$P(\text{Drugs} \mid \text{Pos}) = \frac{P(\text{Pos} \mid \text{Drugs})P(\text{Drugs})}{P(\text{Pos} \mid \text{Drugs})P(\text{Drugs}) + P(\text{Pos} \mid \text{No Drugs})P(\text{No Drugs})}$$

Bayes' law supplies a mechanism for reversing conditional probabilities; that is, given the true positive and false positive values of 0.99 and 0.05 ($P(\text{Pos}|\text{Drugs})$ and ($P(\text{Pos}|\text{No Drugs})$, respectively), we are able to obtain the *posterior* probability that drugs were present given the positive test result. Another way to think of the posterior probability is to consider it as the conditioned probability that the worker was under the influence of drugs, taking into account all of the associative data along with the positive test results.

Thus, applying Bayes' law,

$$P(\text{Drugs} \mid \text{Pos}) = \frac{(0.99)(0.02)}{(0.99)(0.02) + (0.05)(0.98)} = \frac{0.0198}{0.0198 + 0.0490} = \frac{0.0198}{0.0688} = 0.2878;$$

that is, the posterior probability of drugs given a positive test result is just under 0.29. While this result represents a substantial upward revision from the prior probability of 0.02, it is dramatically less than the sensitivity of the test, $P(\text{Pos}|\text{Drugs}) = 0.99$. One way to help understand this counter-intuitive conclusion is to note that the posterior probability represents the ratio of correct positive tests to all positive tests. In light of the low prevalence of drug use among the relevant population in the example, most (2 out of 3) of the positive tests will be false positives. For example, if 10,000 workers were tested, 98% or 9800 would not have drugs present and 5% of those or 490 would falsely test positive, while 2% or 200 would have drugs present and 99% of those or 198 would correctly test positive. Thus only 29% or 198/(198 + 490) of all positive tests would be true positive tests.

When Bayes' is used in a criminal proceeding as a measure of guilt associated with a piece of evidence the prior probability of guilt may reasonably be assigned a value of 0.5, meaning that the probability of guilt is then conditioned in a vacuum of unrelated evidence favoring guilt or innocence. Another perspective is that to use a prior probability other than 0.5 is to count evidence twice; first in using it to arrive at a prior probability and then again when it is presented in court.[12] Bayes' equation becomes simpler when the prior probability of an occurrence is 0.5, as this allows for the prevalence in the numerator to cancel out the (1 − prevalence) value in the denominator, reducing the equation to the following:

$$P(\text{Guilt} \mid \text{Evidence}) = \frac{(\text{sensitivity})}{(\text{sensitivity}) + (1 - \text{specificity})}$$

This formula is also known as the positive predictive value (PPV), in which all of the true positives are divided by the sum of the true positives and the false positives and gives the probability that a positive test is correct.

3. Case study presentation

The following case study illustrates a practical application of Bayes' law in a vehicular homicide investigation in which the probability that the suspect was in the driver's seat was assumed to be equal to the probability that the suspect was guilty of vehicular homicide. The facts in the case, as presented below, are ideally suited for a Bayesian analysis because they can be evaluated as a series of probabilities that all bear some relation to the ultimate question of the defendant's guilt or innocence. A brief summary of the facts of the case is as follows: two men were front seat occupants in a full-sized Ford pickup that left the right side of the roadway and collided with a tree at approximately 60 miles per hour, sustaining a speed change at impact of more than 50 mph, then rolling one quarter turn clockwise onto the passenger side. At the point of impact one of the occupants was ejected, the vehicle burst into flames, and the occupant inside the vehicle was incinerated (see Fig. 1). The ejectee, who was found to have a blood alcohol concentration (BAC) of 200 mg/dL (the legal BAC limit in the jurisdiction where the collision occurred was 80 mg/dL), claimed to have been unrestrained and asleep in the passenger seat at the time of the collision and that the decedent was driving. There was no collateral evidence as to who was driving the vehicle, such as witness statements or vehicle ownership (the pickup belonged to the company that both occupants worked for).

A Bayesian analysis allowed for an evaluation of the collective probabilistic weights assigned to the various pieces of evidence that conditioned the probability that the ejectee was the driver versus the passenger. The mutually exclusive nature of the "who's

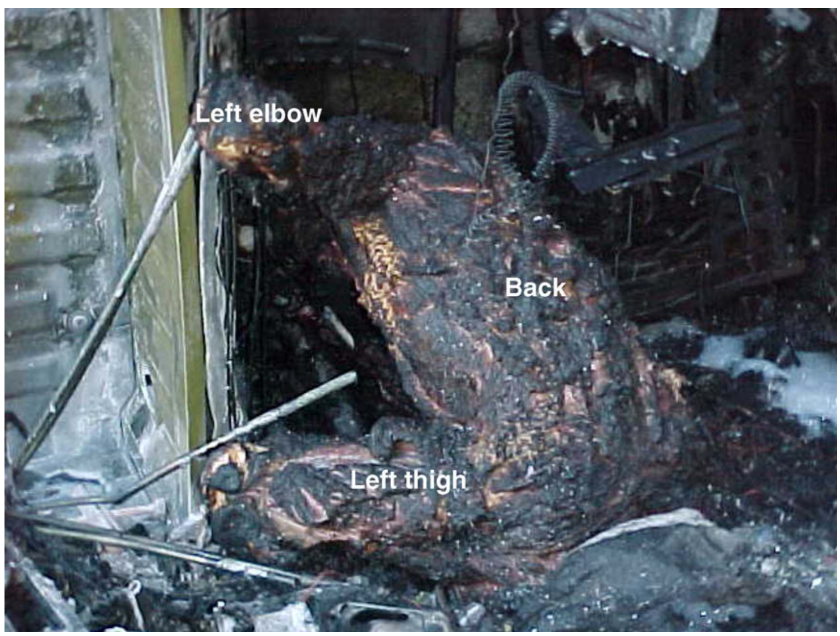

Fig. 1. The occupant *in situ* after the roof of the pick up was removed. The pick up bed is to the left of the photograph and the frame of the incinerated passenger seat is to the right of the decedent.

Fig. 2. The vehicle at final rest on its passenger side. The arrow indicates the extensive crush to the left front of the vehicle.

Fig. 3. The toe pan on the driver's side was crushed to approximately 8 in. from the front edge of the driver's seat, a loss of nearly 2 Ft of leg space.

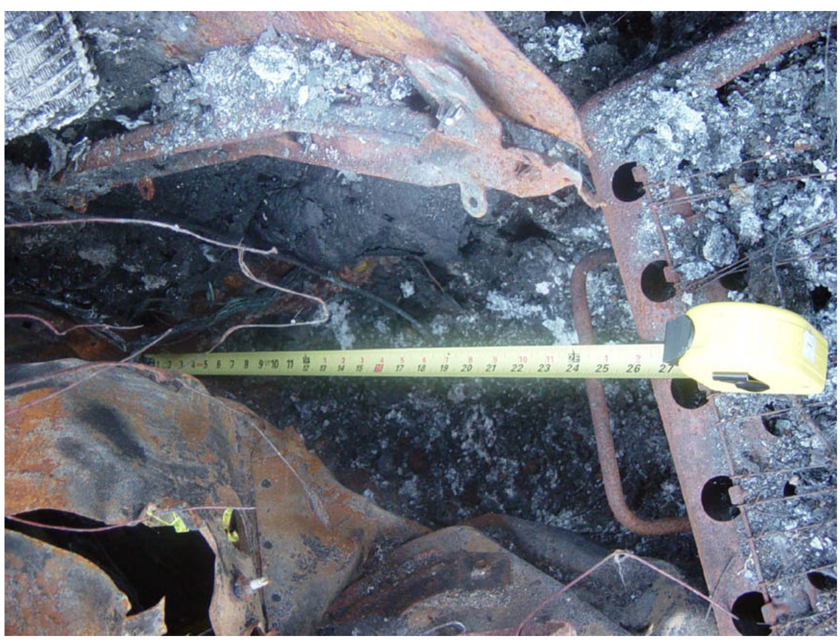

Fig. 4. The toe pan on the passenger's side was well preserved, with more than 2 Ft of leg space.

driving" scenario meant that the probabilistic weight of evidence placing one occupant in the driver's or passenger's seat would be equal to the weight placing the other occupant in the passenger's or driver's seat. The following evidence was undisputed in the case.

1. The front end of the vehicle was extensively crushed on the driver's side, resulting in intrusion that eliminated virtually all the driver's-side toe pan. In contrast there was little front to back intrusion on the passenger side, and the majority of the passenger's-side toe pan was preserved (see Figs. 2–4).
2. The airbags deployed in the vehicle, as the deployed passenger airbag was identified among the wreckage (see Figs. 5 and 6). The driver's-side airbag was not recovered due to fire damage, however, barring failure, the probability that it deployed was 100%, given the deployment of the passenger airbag.
3. Field examination, gross post-mortem examination, and radiographic examination of the decedent failed to reveal any lower extremity fractures (see Fig. 7).
4. The ejectee was diagnosed with high-energy (comminuted and/or open) fractures of the right femur, tibia, fibula, and foot (see Fig. 8).
5. The only apparent opening created by the crush damage was through an opening between the driver's side door and the A-pillar (see Fig. 9).

Fig. 5. A view of the passenger side of the vehicle after it was raised to an upright position. The section in the white square is magnified in Fig. 6.

Fig. 6. The passenger airbag (the lighter structure with the stitching) was preserved from the fire and found embedded in dirt and grass.

The ejected survivor was charged with vehicular homicide, taking into account the following conclusions:

1. The opening on the driver's side of the vehicle offered a plausible ejection route only for an occupant in the driver's seat;
2. The deployment of the airbags would have made a passenger ejection through the windshield highly improbable as a result of the initial collision with the tree, and the subsequent ¼ roll-over to the right would have had the effect of trapping rather than ejecting an occupant in the passenger's seat;
3. The extreme intrusion observed in the toe pan on the driver's side made a lower extremity fracture highly likely in an occupant in the driver's side, and the ejectee's lower extremity injuries were consistent with this assumption. Conversely, the lack of intrusion on the passenger's-side made a lower extremity fracture less likely, and this was consistent with the lack of bony fracture seen in the decedent. This Injury Pattern Analysis points very strongly to the ejectee as the driver.

While the above findings make it probable that the ejectee was the driver, one must be cautious against a conditional probability fallacy related to any of the above three conclusions. For example, if it is reasonable to state that there is a 95% probability that an occupant in the driver's seat will sustain a lower extremity fracture, how does one avoid fallacy by reversing the probability and concluding that there is a 95% probability that the ejectee is guilty? A Bayesian approach is ideal for such an analysis, resulting in the conditioned probability that the ejectee was the driver:

4. Bayes' equation

The Bayes' equation for the vehicular homicide investigation is approached like the drug test above, except that there are four pieces of evidence that can be considered as test results for the guilt of the ejectee: the presence of fracture in the ejectee, the absence of fracture in the decedent, the high opportunity for driver ejection, and the low opportunity for passenger ejection. Just as with the drug test example above, we have a positive test result (4 positive results, actually) that we think is indicative of guilt, but a Bayesian approach is needed to condition the test result with the true positive rate (sensitivity) and the false positive rate (1-specificity) of the tests in order to avoid a conditional probability fallacy. A major difference between the drug test example and the vehicular homicide case is that we have to take into account the fact that there are four independent test results, rather than just one. The Bayes' equation allows us to do just that.

Fig. 7. Neither field examination nor radiographic evaluation revealed lower extremity fractures in the decedent.

Fig. 8. The ejected survivor was found to have high-energy fractures of the femur, tibia and fibula, and foot.

The end result of interest, the posterior probability that the ejectee was the driver and thus guilty conditioned by the sensitivity and (1 − specifity) of the tests for guilt, is expressed as P(Guilty|Tests). The other elements of the Bayes' equation are assigned the following values:

The prior probability that ejectee/defendant was driver and the decedent was the passenger = 0.5.

The prior probability that ejectee/defendant was the passenger and the decedent was the driver = 0.5.

(*NB*: since these two values are identical and are present in the numerator and the denominator of the Bayes' equation they cancel each other out and therefore will not be used in the calculation of the posterior probability of guilt. Thus, the abbreviated Bayes' equation presented above as the positive predictive value will be used for the case study).

The following four positive test results are included in the Bayes' equation:

4.1. Test #1

Test #1 is based in the evidence of a fractured lower extremity in the ejectee in the presence of explanatory extensive driver's side vehicle damage. The sensitivity of this test is equal to the probability that the ejectee would have sustained a fracture given that he was the driver. This probability was estimated to range from 0.85 to 0.95, and was derived from the literature as follows: a study of 339 injuries resulting from frontal collisions with occupant compartment intrusion and unbelted occupants reported an injury rate, including lower extremity fracture, of 32% at <25 mph ΔV, 46% at 25–30 ΔV, 61% at 30–35 ΔV, and 82% at >35 mph ΔV.[17] At the >50 mph ΔV that was determined for the subject collision it was considered reasonable to assign a low value of 0.85 and a high of 0.95 as the probability of lower extremity fracture for the driver position.

Fig. 9. The induced crush seen in the driver's-side door (striped arrow) and A-pillar (notched arrow) formed a large opening and potential ejection route for the driver between the windshield and the door. The space indicated by the double arrow is greater than 2 Ft.

The false positive rate or (1 − specificity) of Test #1 is the probability that the ejectee would have a fracture given that he was in the passenger seat and is estimated to range from 0.56 to 0.63. This value could not be extrapolated from the literature, however a query of the National Automotive Sampling System (NASS) database (conducted for the investigation) for lower extremity injury frequency in passengers versus drivers in higher speed left frontal collisions indicated a 52% greater injury rate for drivers than for front seat passengers. Extrapolating this figure to the 0.85–0.95 driver fracture probabilities yielded 0.56–0.63 for passengers. The figure is a likely over-estimation of the actual false positive rate (thus favoring the ejectee as the passenger) as there are relatively few collisions in the NASS at a 50 mph ΔV that fulfilled the inclusion criteria for the analysis, resulting in a sample with a lower average ΔV than that of the subject crash and correspondingly lower intrusion and thus fracture rate.

4.2. Test #2

Test #2 is based on the lack of fracture found in the lower extremities of the decedent combined with the corresponding lack of damage to the vehicle on the passenger side. Test #2 is the mirror image of Test #1, but because of the mutually exclusive nature of the "who was driving" scenario the evidence can, in essence, be counted twice (this is because the injury status of the passenger is independent of the degree of damage to the driver's side, and vice versa). The sensitivity of Test #2 is equal to the probability that the decedent would not sustain a fracture given the passenger seat position. This value is equal to the specificity for Test #1, or 0.37–0.44.

The false positive rate (1 − specificity) of Test #2 is the probability the decedent could have been in the driver's seat and not sustained a fracture. This value is the equivalent of (1 − sensitivity) of Test #1, or 0.05–0.15.

4.3. Test #3

Test #3 is based on the undisputed fact that the defendant was ejected and that the reconstruction of the collision indicated that the most likely ejection route was on the driver's side.

The estimated true positive rate or sensitivity of Test #3 is 0.5–0.75. There are no well-defined data sets that fit the unique characteristics of the subject collision and thus this probability was estimated based upon the reconstruction of the collision, the occupant kinematics, passive restraint use (none), active restraint deployment (driver's side airbag most probably deployed given the passenger airbag deployed), and available ejection routes collectively considered. During the subject collision with the tree the vehicle suddenly slowed and rotated counter-clockwise by 15–20° before rebounding and rolling ¼ turn onto its passenger side. The occupants would have moved forward and to the left relative to the vehicle interior at the same time that the airbags deployed. This movement would have directed the driver toward the available ejection route between the A-pillar and the doorframe demonstrated in Fig. 9. The movement of the driver to the left would have been potentially augmented by interaction with the left side of the deploying and expanding airbag, propelling the driver toward the gap. If the driver was not ejected during the initial impact with the tree there was no subsequent mechanism for ejection in the subsequent rollover, as the occupant would have moved toward the passenger side of the vehicle and been effectively confined in the vehicle when the passenger side door was trapped against the ground.

The false positive rate for Test #3 is the probability that the ejectee could have been ejected from the passenger seat of the vehicle and is estimated at 0.05–0.15. This probability is given a very low value because the reconstruction of the collision events produced no identifiable route through which the passenger could have been ejected. The passenger side airbag deployment would have made an ejection through the windshield in the initial impact with the tree highly improbable. The subsequent vehicle rollover to the right would have moved the passenger somewhat to the left relative to the vehicle interior and thus toward the opening between the A-pillar and the driver's door frame. While it is possible that the passenger could have been ejected through this opening, the probability of the passenger being ejected past the driver without the driver also being ejected is very low. This value is the same as (1 − specificity) for the driver's side ejection test.

4.4. Test #4

Test #4 is based on the fact that the decedent was not ejected and that the reconstruction of the collision events did not identify a reasonably probable ejection route for an occupant in the passenger seat. As was the case with Test #2 relative to Test #1, Test #4 is the mirror image of Test #3. Thus, the sensitivity of the Test #4 is the same as the specificity of Test #3, the probability of no ejection for an occupant in the passenger's seat (0.85–0.95).

The false positive rate for Test #4 is the complement of the sensitivity of Test #3 (1 − sensitivity), and thus is 0.25–0.5.

Notice that the structure of these probabilities is similar to the preceding drug test example, except that the values are given in a range to represent the lack of certainty behind the estimates.

The computation of the posterior probability that the ejectee was driving is a generalization of the calculations for the single test (drug test) example under the major assumption that fracture and ejection are independent events. Although an argument can be made that the fracture and ejection are not necessarily independent as a general principle, particularly when the fracture results from the ejection, in the facts in the case study they are strongly correlated with differing reconstructed injury and kinematic mechanisms (fracture due to toe pan crush, ejection due to lack of restraint, presence of airbag barrier, and door frame deforma-

tion). Thus the assumption of independence is reasonable given the facts in the present case.

As mentioned earlier, the value of the 0.05 value for the prior probability of both guilt and innocence simplifies the Bayes' equation so that it is the equivalent of the positive predictive value equation. Recall that this equation is

$$P(\text{Guilt} \mid \text{Tests}) = \frac{(\text{sensitivity})}{(\text{sensitivity}) + (1 - \text{specificity})}$$

or more simply:

$$P(\text{Guilt} \mid \text{Tests}) = \frac{(\text{true positives})}{(\text{true positives}) + (\text{false positives})}$$

From the discussion of the tests above we have estimated the sensitivity or true positive rates in the following ranges:

Test #1 = 0.85–0.95
Test #2 = 0.37–0.44
Test #3 = 0.5–0.75
Test #4 = 0.85–0.95

The $(1 - \text{specificity})$ or false positive rates were estimated as follows:

Test #1 = 0.56–0.63
Test #2 = 0.05–0.15
Test #3 = 0.05–0.15
Test #4 = 0.25–0.5

For the Bayes' calculation to maximally favor the defendant only the lowest true positive and highest false positive values are used. The posterior probability of guilt using the PPV equation from above is calculated as follows:

$$\begin{aligned} &P(\text{Guilt} \mid \text{Tests}) \\ &\quad = \frac{(0.85 \times 0.37 \times 0.5 \times 0.85)}{(0.85 \times 0.37 \times 0.5 \times 0.85) + (0.15 \times 0.63 \times 0.5 \times 0.15)} \\ &\quad = \frac{0.1336625}{0.1336625 + 0.0070875} = 0.949645. \end{aligned}$$

Thus, in the crash and evidence scenario described, the test results are highly persuasive in establishing the ejectee as guilty, revising the prior probability of guilt from 0.5 to 0.949645. The astute reader will note that because 0.5 was used both for the true and false positive rate for Test #3 in the above equation they cancel each other out, further simplifying the calculation.

As an alternative to a probability, the likelihood that the ejectee is guilty can be expressed in terms of posterior odds, the ratio of the posterior probability that ejectee is the guilty to the posterior probability that he is innocent. The posterior probability of the innocence of the ejectee is calculated by $(1 -$ the posterior probability$)$ that he is guilty. Thus the posterior odds that the ejectee is guilty of vehicular homicide are expressed as follows:

$$\text{Odds}(\text{Guilt} \mid \text{Tests}) = \frac{0.949645}{(1 - 0.949645)} = 19$$

A simpler way to arrive at the same result without the need to convert the probability to an odds ratio is to incorporate the odds into the calculation in the form of a likelihood ratio (LR).[18] The LR for the above calculation is the ratio of the product of the true positive rates for all of the tests to the product of the false positive rates for the all of the tests. If the LR for the test for guilt is multiplied by the prior odds of guilt then the resulting value is the posterior odds of guilt. Recall that the prior probabilities of both guilt and innocence were 0.5, and thus the prior odds of guilt is the ratio of the probabilities, i.e. 0.5:0.5, or 1. The simplified calculation using the test LR is as follows:

$$\begin{aligned} \text{Odds}(\text{Guilt} \mid \text{Tests}) &= \frac{0.5}{0.5} \times \frac{(0.85 \times 0.37 \times 0.5 \times 0.85)}{(0.15 \times 0.63 \times 0.5 \times 0.15)} \\ &= \frac{0.06683125}{0.00354375} = 19 \end{aligned}$$

The posterior odds indicate that, using the data most favorable to the defense, the ejectee is at least 19 times as likely to have been the driver versus the passenger, and thus it is equally probable that he is guilty, a conditioned conclusion that can be drawn without fear of committing a conditional probability fallacy or the Prosecutor's Fallacy (as an incidental note, had the Bayes' calculation been performed using the data most favorable to the prosecution [the highest true positive values and lowest false positive values] the result would have been odds of 284–1 in favor of guilt).

In order to meet the fact finder's criterion that a defendant is guilty "beyond a reasonable doubt" we suggest a threshold posterior probability of 0.91 or more, the equivalent of posterior odds of 10–1, as this is roughly the equivalent of a 90% confidence interval. By this standard, the Bayesian analysis presented herein easily proved that the ejectee/defendant was driving, and thus guilty beyond a reasonable doubt.

9. Conclusion

The proper evaluation of probabilities associated with evidence in a vehicular homicide investigation requires a method for conditioning and weighting the probabilities and also for assessing the interaction of the probabilities. Forensic epidemiology is a systematic framework that provides for such evaluation; firstly, probabilities can be assessed with the use and interpretation of epidemiologic data, when it is available. Secondly, the interaction of the probabilities can be assessed with the application of Bayes' law. The case study presented in this paper is intended to afford a practical method of assigning probabilistic values to evidence discovered in the course of a vehicular homicide investigation. Once the probabilities are properly conditioned by all of the available and pertinent evidence they can be put into a Bayes' equation and the resulting posterior odds can be used to inform a fact finder as to the collective strength of the evidence relative to the "beyond a reasonable doubt" standard. Without such a methodologically sound approach the much greater risk of committing a conditional probability fallacy or Prosecutor's Fallacy in the interpretation of the evidence cannot be ignored.

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